Comparative evaluation for detection of brain tumor using machine learning algorithms

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ABSTRACT

Automated flaw identification has become more important in medical imaging. For patient preparation, unaided prediction of tumor (brain) detection in the magnetic resonance imaging process (MRI) is critical. Traditional ways of recognizing z are intended to make radiologists' jobs easier. The size and variety of molecular structures in brain tumors is one of the issues with MRI brain tumor diagnosis. Deep learning (DL) techniques (artificial neural network (ANN), naive Bayes (NB), multi-layer perceptron (MLP)) are used in this article to detect brain cancers in MRI data. The preprocessing techniques are used to eliminate textural features from the brain MRI images. These characteristics are then utilized to train a machine-learning system.

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1. INTRODUCTION

In the age of e-healthcare and information technologies, physicians will deliver quality health care to their patients [1]. This research discusses the problems relating to the segmentation and management of dysfunctional usual tissues [2], [3], and brain tissues, such as grey matter (GM) processes, detection of white matter (WM), and controlling of cerebrospinal fluid (CSF) from applicable magnetic resonance (MR) imaging techniques and photos utilizing a support vector machine (SVM) classifier and applicable feature extraction technique [4]. The tumor is defined as an unregulated and uncontrolled growth of cancer cells or expansion grid [5]. Concept of brain tumor is considered an uncontrolled or unmaintained growth of cancer or malignant cells. In simple forms, a brain tumor can be of two types, benign growth and forms of malignant growth [6]. For patients, forms of benign brain tumors are structurally standardized including no active (cancer) cells [6]. In patients, malignant brain tumors are structurally non-uniform (heterogeneous) including forms of active cancer cells. Gliomas and meningioma are manifestations of forms of low-grade tumors and growth known as benign tumors [7].

On the other hand, glioblastoma and astrocytoma are considered high-grade growth tumors classified as malignant tumors [8]. According to World Health Organization (WHO) and, brain tumor association of American Brain Tumor Speculation (ABTA), the most popular and accepted mode of classification scheme utilizes grade I and grade IV scales to distinguish different forms of benign growth and malignant tumor growth forms [9]. Benign cancers fell below stages of grade I (categorized) and grade II glioma growth on this scale, and different forms of malignant tumors growth fall below grade categorization of III growth and graded under IV glioma growth.

Grade I and II tumors tend to grow slowly, while grade II tumors tend to grow rapidly [10]. If a low-grade brain tumor is not handled, it will progress to a high-grade brain tumor, which will then become a malignant form of brain tumor showing irregular and uncontrolled growth. Patients with different forms of grade II gliomas can be watched closely and have the magnetic resonance imaging (MRI) or computer tomography (CT scans) every 6 to 12 months [11]. Every person, at any age, may be affected by a brain tumor, and the effects on the body vary from person to person. Low-grade categorized as I and II glioma (uncontrolled growth) benign tumors are considered to be curable following a complete surgical procedure in this process, while grade III and IV forms of malignant brain tumors may be treated with different forms of radiotherapy procedure, chemotherapy treatment, or a combination of the two treatment procedures [12].

Both type III and IV glioma, also known as anaplastic astrocytoma, are used in the term malignant glioma. Anaplastic astrocytoma is a mid-grade tumor with irregular or uncommon growth features and a higher growth index than most low-grade tumors [13]. Glioblastoma is also the most dangerous form and type of astrocytoma seen among the patients, as well is categorized as the highest grade glioma in this category. Glioblastoma is distinguished from other tumor types by the abnormal and uncontrolled forms of accelerated growth of different types of blood vessels and the presence of uncontrolled types of necrosis (dead cells) around the tumor segment in the patient [14]. Glioblastoma which is an extremely uncontrolled form of growth, at the grade IV tumor stage, is a fast-growing and highly contagious, and malignant tumor type as contrasted to other tumor groups via different types of medical imaging methods, segmentation is used to detect infected tumor tissues [15]. Segmentation is a way of separating and differentiating a picture into different blocks in terms of sharing common properties, such as color, shape, growth, structure, contrast, brightness, development, border, and grey level in the patients [16]. It is a significant step in the processing of pictures. The method of separating and differentiating different forms of tumor tissues such as oedema and dead cells formation, from normal brain tissues and healthy tumors is categorized as different developmental stages for WM, GM, and CSF using MR images or other imaging techniques is known as segmentation of brain tumors [17].

2. THE COMPREHENSIVE THEORETICAL BASIS

2.1. Detection and identification of brain tumors in MRI imaging

The MRI brain images to detect brain tumors are reprocessed using a median filter, during which the brain tissue is analyzed through morphological segmentation and tumor extraction techniques [15]. This is a great way to provide an accurate MRI picture of the tumor, (detection, determination, identification, and classification of brain tumors in MR images by) explains how to use the neuro-fuzzy classifier to extract the tumor portion of the brain image [18], after which features were computed from the extracted texture using the gray level development and formation of co-occurrence procedure matrix process (GLCM) neural networks and segmentation systems detected tumors [19]. The patient controlled analgesia (PCA) is used for function extraction and the derived features of MRI. And the typical recognition rate is around 88.2%, whereas the best recognition rate is about 96.7% In their attempt to use picture the brain tumors, Rajesh and others suggested a segmentation strategy, which employs the probiotic neural network (PNN) to classify the MRI scans [19]–[21]. The PNN recommended handling the naming of brain tumors with greater finesse Suchita and Lalit, developed an unsupervised learning procedure for photographs of the human brain through the use of the positron emission tomography (PET) scanner [22]. Until they are analyzed, the MRI images are thresholded, noise is removed, and the tumor is segmented [23]. The brain's structure is detected and maintained by using and incorporating the GLCM method which is widely used for image processing, development, determination, and subsequent self-organizing mapping (SOM).

2.2. Brain tumor types

A tumor is generated by a rise in the number of cells without being balanced out by a decrease in the number of neuron deaths a tumor in the human brain can exert a strong influence over the whole body, including the skull, and can lead to impairment in the human health. The numbers of brain tumors increase daily [21]. To improve treatment, detection early on is vital for all brain tumors, as it is for all diseases. Early detection of brain tumors is also discovered through the use of MRI. MRI does not include the introduction of drugs, is painless, is done with low doses of radiation, and does not expose the patient. The normal MRI scanning sequence consists of axial, coronal, and sagittal views. The MRI imaging allows for three imaging modalities to be used to provide more detailed details on the tumor structure, tissue, and thickness [24]. The three-dimensional (3D) phase MRI scan can be run in three separate ways. A 3D brain MRI scan of biological tissue with a single-sequence MRI may not be able to distinguish between these two kinds of tumors. MR imaging has two sequences, T1- and T2 weighted. T1-weighted MRI helps identify brain tumors that have shifted to the cerebral spinal fluid spaces. The contrast used in T2-weighted MR imaging is used to depict pathology on the other side is heavy. Brain tumors may be found nearby. Thus, the tumors are given names based on which will classify them according to the types of cells. Tumors are usually found in the brain and pituitary gland as the name indicates, glioma is a disease that affects the brain and the spinal cord. Gliomas originate in the glial help cells of the brain. It's a tumor that occupies the brain, but is still able to shape itself in the membrane of the dura, and arises from the membrane. One of the most often occurring brain tumors in adults is of this kind is found to include between 15-20% of brain tumors [21]. Finally, a pituitary tumor grows in the pituitary gland, which establishes hormonal equilibrium, which in turn regulates the activity of other glands, which includes a portion of the menstrual cycle. T1-weighted MRI with three differentiating the tumor groups using MRI to diagnose brain tumors leads to wasted time and misdiagnoses [25]. Deep learning (DL) and image recognition algorithms are already used in recent computerized MR diagnostic programs to cut both the time and the margin of error a deep learning-based, object recognition technique utilizes multilayered neural networks and is part of the kind of machine learning called artificial intelligence. It is possible for DL to learn from the same kind of data as machine learning algorithms do: images, video, and text as well as when used by conventional techniques [24], but these are significantly different approaches to solving the problem. In this research, we seek to build a web-based program that is capable of using an in-depth T1 MRI scan for glioma, meningioma, and pituitary adnexa classifications through DL so are suspected that health practitioners and scientists can now easily diagnose brain tumors because of the free web-based tools created Often, this web-program can be used as a diagnostic tool for brain tumor classifications (i.e., glioma, meningioma, pituitary). The experimental findings show that all measured indicators can distinguish the various categories of brain tumors on the training dataset, which is significantly higher than 98%. However, for all indicators the score is greater than or equal to 91%, except for sensitivities and the major complication or comorbidity (MCC) for meningioma. On the preparation and evaluation points, the convolutional neural network (CNN-based) model can accurately identify the various brain tumor forms [26], [27]. An intriguing thesis on CNN is researching brain tumor classifications on public MRI pictures, which used the technique of DL to a group over 3,400 different T1-weighted images of the same subjects into 233 and 3,000 exclusive models. When run on two different datasets, the evolved method produces overall accuracy of 96.13% and 98.7%.

2.3. Method for detection

Results from an empirical research survey show that automatic brain tumor diagnosis is critical where there is a human existence at stake [21], [28]. Figure 1 shows the usable method for detecting brain tumors, starting with image acquisition, preprocessing, extraction and segmentation. Function extraction and classification is the technique that is widely used to diagnose cancer in MRI photos using a machine learning algorithm.

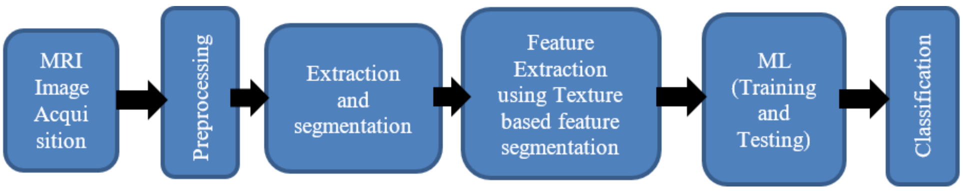


Figure 1. Usable method for brain tumor detection in MRI imaging

2.3.1. Image acquisition stage for MRI

In the initial stage, the MRI images for brain scanning are gathered, which also works as the input for the pre-processing stage for the overall interconnected system [22]. In this stage, different forms of sample images are collected for relevance. In the image acquisition and development stage, consequent management of the performance metrics is ensured [29]. In Figure 2 shows the normal brain MR image refers to non-tumour images.

2.3.2. Preprocessing

Preprocessing offers gain by refining some of the image functionality for eventual processing [24]. Until processing the MRI pictures, the following measures are applied: As seen in Figure 3(a), the red, green, blue (RGB)-formed MRI image is first normalized into greyscale and then subjected to median filtering Figure 3(b). Since more precise analysis is needed, the noise has been filtered out. Canny edge identification and detection method as depicted in Figure 3(c). To segment the picture, the edge detected image is needed. The picture in Figure 3 is a procedure used to find the tumor's position in the brain's watershed segmentation Figure 3(d). The segmentation of a picture is a series of segments. Segmentation seeks to reorganize picture representation [24]. A marked picture in the product of watershed division in graphic, all the objects and tools will have different values will be on the same scale, all the first object's pixels will have value 1, all the second object's pixels' first, all other objects' pixels will have a second value [30], and so on This chart shows in Figure 3 illustrates numerous preprocessing techniques applied to brain MR images.

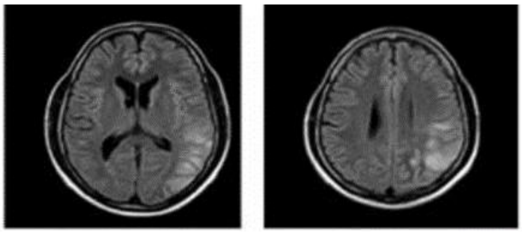
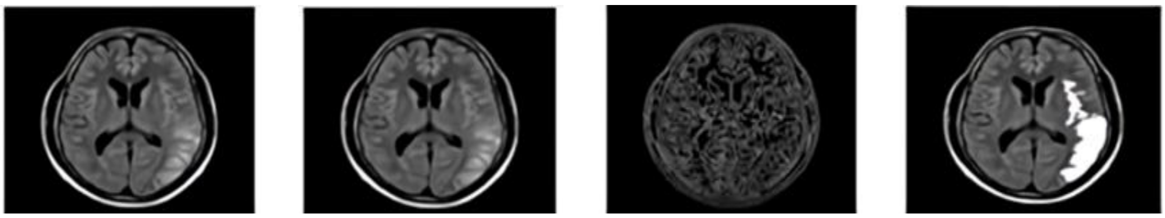


Figure 2. Brain MR image (samples)



(a) (b) (c) (d)

Figure 3. Stages in preprocessing of MRI images (a) original image, (b) filtered image, (c) edge detected image, and (d) segmented image

2.3.3. Feature extraction

When an algorithm handles massive volumes of input data and dramatically simplifies it down to only a few functions, it is claimed to reduce to a function vector [31]. Feature extraction involves the transformation of input data into a series of functions of function extraction the texture segmentation approach is used, and the extracted forms of textural features are depicted in the segmented MR image [32]. The GLCM process is a versatile tool of exceptional efficiency, used to remove these characteristics [33]. The GLCM tools for the identification of texture extraction process is very capable and used for the development and identification process as it uses fewer grey levels while improving the overall classification [34]. To further identify and distinguish between usual and abnormal conduct, the gray level measurement and co-occurrence (GLC) features are used [35]. There are details to be found in texture about the way objects are placed on the floor. Grey tone spatial features have more general applicability to picture classification relevance.

2.3.4. Classification

In certain cases, multi-layer perceptron (MLP) and a naive Bayes (NB) algorithm are used to perform pattern recognition on photographs of the brain [36] to help them learn and make better decisions This method involves creating an artificial neural network (ANN) [37] in which multiple layers map inputs to a single output variable that feeds to a second one or multiple subsequent layers until a suitable response is reached. Each neuron in the MLP is regulated by its special activation mechanism [29]. A feedback circuit is known as a feedforward since it has no feedback [36]. It's all in the journal. When the goals for success and actual results align, learning occurs by changing the association weights [38]. Because of this negative feedback, [39] the system is known as derisively as 'backward pathogenesis'. As a goal, the total weight values must be minimized such that each edge has a lower chance of error. Figure 4 show result of all the mentioned stages, the result of the preprocessed image Figure 4(a), k-means segmented image result shown in Figure 4(b), fuzzy c-means segmented image shown in Figure 4(c), clear border result in Figure 4(d), and feature extracted image in Figure 4(e).

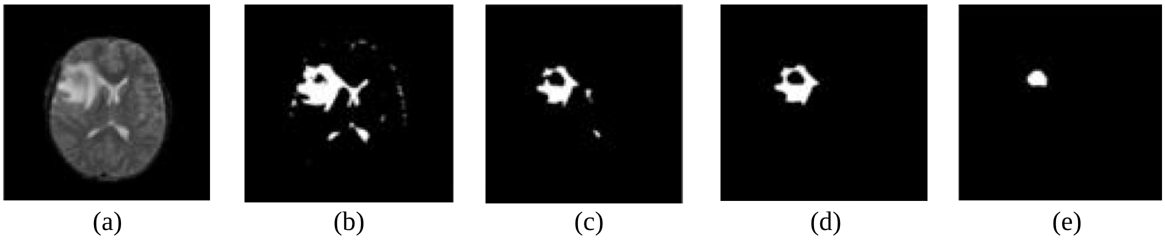


Figure 4. Classification for different MRI outputs, (a) original image, (b) k-means segmented image, (c) fuzzy c-means segmented image, (d) clear border, and (e) feature extracted image

3. METHOD

3.1. Methods and eligibility criteria

A systematic review and comparative study have been conducted based on the acceptability and relevance of the user data and speculation for the research process. Different methodological perspectives of the research have been adopted effectively to analyze the findings. For allocating research and maintaining the research process [40], research philosophy, research design, and ethical processes have been selected aligning with the requirements of the research.

3.2. Search criteria

The search technique in this research is an organized structure of main words used to search the target database. The search approach incorporates findings and the core principles of the target search query to obtain correct answers. Prominent databases such as the Institute of Electrical and Electronics Engineers (IEEE), Journal of Science and Technological Researches (JSTR), and the International Institute for Science, Technology and Education (IISTE) have been included in the search strategy. The search criteria prioritized the relevance of the topic with the objectives of the current research. Search criteria are based on: i) articles published between 2012 and 2021 have been selected for this research; ii) databases such as word elektrik browser (WEB) of science, IEEE, JSTR, IISTE, and employee database (EMBASE). have been taken into consideration for this research; and iii) keywords such as brain tumor, screening brain tumor, detection techniques, and MRI image. have been used for the search purpose, using or, and criteria based on the assessment criteria and requirements of the research.

3.3. Ethics

Different ethical contexts have also been addressed in this research to assess the findings effectively. Selection of the articles and journals have been conducted based on the reliability and acceptability of the published articles. To assess the ethical contexts, different criteria for the research processes have been addressed effectively.

3.4. Protocols and procedures

In this research, protocols, and procedures have been selected carefully to maintain the acceptability and reliability of the research [40]–[46]. In this systematic review of articles, different dimensions for reliability and validity have been addressed accordingly. To analyze the concepts of the evaluative tactics and strategies to detect brain tumors from screening MRI images, a comparative tool for the selection of articles has been taken into consideration. Appropriate procedures and protocols have been selected in this regard.

4. RESULTS AND DISCUSSION

4.1. Excerpts from prominent research

To present some of the comparison points, Table 1 shows the details of the comparison of some research work in the field of the machine learning approach for detecting brian tumours. The analysis is based on the outcomes of the individual research works. Table 1 shows comparison of several papers based on the detection mechanism.

4.2. Discussion

Cancer that has developed in the brain is called a brain tumor [31]. Benign and malignant tumors may be located in the brain. Clustering is commonly used in the diagnosis of diseased tissues. It is recognized that low-grade I and high-grade gliomas are considered to be curable [32]. Tumors with grade III and IV properties are usually are well-tolerated by radiotherapy and chemotherapy [33]. Glioblastoma is the most dangerous and the most category form of astrocytoma [35]. Grade IV glioma is a very malignant tumor with a high incidence of grade V metastasis. the procedure of differentiating the tumor from normal brain tissue, for example.

Imaging or pictorial analysis is central to the modern body of knowledge. It's very hard to get your hands around the procedure of making some kind of graphic presentation. Unless otherwise stated, visualizations of the feature are referred to as medical imaging in this section. Algorithms can resolve complicated medical imaging issues to some degree. An embedded co-processor uses a converter that converts an algebra to a hard-wired arithmetic algorithm. Because the geometry of an application's artifacts is quite good, very effective, it would likely be very inefficient through the use of computer graphic modeling. Since conformal geometry does have a defined geometry at a coordinate-free stage, it might be able to meet these problems to a significant degree. Potential is greater than the number. a procedure that is effective and precise in terms of both detection and measurement of three- and registration of 3D shapes you don't have to be overly complicated with free curves and free surfaces. The iterative closest point (ICP) approach will accommodate the most freedom and is built on iterative calculations. There are around a million sums or contractions in the framework profile. A 4-dimensional (4D) image of elements or 4 sets of 4 elements conformal geometric algebra is used for the initial detection of the tumor when running on a general-purpose processor. Neural networks can be used to detect some anatomical features of the tumor this is effective when applied to colored photographs as well. The processing time required for this algorithm can be very short, as long as it is there are few photographs. Even, as well as the tumor volume, we detected with the aid of the form and diameter of the detected tumor using the methodology is more efficient, but it cannot overcome high computational costs.

Table 1. Comparison among the research works

Authors	Findings
Sharma *et al.* [12]	This paper proposes and incorporates machine learning algorithms to assist in brain tumor detection. It is possible to increase the accuracy and granularity of the data collection by taking into account all texture and force characteristics in addition to the collected information. Concepts are established by the GLCM. In this proposed work, energy is introduced into the skin, along with image contrast, dignity, and homogeneity. Videos for both discrimination and accuracy purposes, the multi-layer peron grouping, distinction, and machine learning methods have a determinant approach that targets the top 2.2% of both, and the Bayesian process returns a classification and accuracy rating of 97.6% (accuracy goal).
Bahadure *et al.* [13]	The creative wave transformation (BWT) was employed in this study to increase the speed and reduce the amount of effort required for image segmentation. The surgical or therapeutic segmentation and diagnosis of tumors using MRI is a big issue, but it is a complicated and lengthy procedure based on skills and knowledge that radiologists cannot help with. Therefore, computer-assisted technology use becomes critical to meeting these challenges. SVM-dependent features are isolated from each segmented tissue to improve classification precision and efficiency. Based on the accuracy, sensitivity, specificity, and basis of dice coefficients, this technique has been evaluated and extensively studied to analyze its efficacy and reliability for brain imaging studies. "They showed that the proposed method can discriminate between healthy and unhealthy tissue images, with 96.51% precision, 94.2% sensitivity, and 97.72% accuracy." Overall, the results showed a dice coefficient of 0.82, with the computer extraction of the tumor yielding more substantial overlap with the manually derived tumor area. In comparison to existing state-of-of-the-the-the-art approaches, the results highlight the accuracy and precision parameters.
Nadeem *et al.* [14]	Medical image recognition, medical image interpretation, and bioinformatics have seen a resurgence with the advent of DL in recent years. Because of this, DL has had a big influence on how malignancies can be detected and quantified in various areas, including brain tumors, the liver, the belly, and the retina. Since it is extremely relevant to brain tumor science, we hope that it can shed light on major principles of DL (e.g., segmentation, classification, prediction, evaluation). Data layers of computational models are processed using DL often incorporating several levels of abstraction. This essay provides a summary of some of the important developments in the study field (i.e., DL in brain tumor analysis). There have been several various forms of areas studied and placed to the test, as well as a taxonomy that has preserved continuity throughout the literature. The following is a timely discussion of DL key weaknesses in this modern technology environment offered as well as a collection of tools on how it can be enhanced for usage in the new media market.
Gore and Deshpande [15]	A brain tumor cannot be managed in the latest stages, since it is the most dangerous disease of all. It should be located by an MRI. What happened to the patient, in other words, means that he/she shifted to stay alive. The words "brain tumor" and "glial glioma" apply to the multiplication of glial cells. In the majority of cases, it's the deoxyribonucleic acid (DNA) that is broken. In the human brain, there are almost ten times as many cells as there are in the whole body. Self-damaged brain cells determine their condition by splitting and reproducing. The MRI produced grey-scale images, in which the nuclei of tumors are colored in darker shades of grey to distinguish between stable and diseased tissue. Given the complexity and lack of uniformity of MRI scans, grey matter-based tumor diagnosis is not reliable. In this effort, we developed a machine-learning algorithm to find tumors. We used CNN and ANN to classify the tumor in the brain. Both un-augmented and augmented databases are included in CNN. The key purpose of the paper is to compare two model predictions about efficiency, precision, and sensitivity, and to choose the better one.

5. CONCLUSION

MRI image techniques used to determine different forms of benign and malignant growths have been an important aspect of the treatment procedures of the patients. In this way, medical professionals can determine the required level of strategic aspects to understand the processes and aspects needed for the treatment processes. To analyze the research outcomes, different aspects of the MRI imaging techniques have been discussed in this report. A brief comparative analysis of the literature has been also conducted to review the findings. The conceptual models use several levels of abstraction to deal with the data in DL algorithms in medical imaging, medical processing, research, and bioinformatics, DL has exploded As several other fields of healthcare have discovered, DL and neural networks have shifted the balance of diagnosis and inference, these advances have had widespread effects on various forms of pathology, such as liver, esophageal, brain tumor, and retinal disease, too As major objectives of this article is to examine the popular applications of DL as it relates to brain tumor research (e.g., segmentation, classification, prediction, evaluation). This book (i.e., DL in brain tumor analysis) contains several research contributions to the area.

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